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13. ABSTRACT (Maximum 200 words) The proposed research will concentrate on how the various magnetometer and induction models Duke has developed can be used to support improved UXO discrimination, especially using multisensor data (e.g. magnetometer, frequency-domain EMI and time-domain EMI). We will utilize the multiple, offset dipole-moment model in the context of UXO classification, utilizing training data to constrain the inversion. Such constraints will be implemented as priors in a Bayesian setting. The classification algorithms will process the model parameters (features) determined by the fit to measured data. The features will be processed by several classifiers, including a likelihood ratio, a support-vector machine (SVM) and a Bayesian relevance-vector machine (RVM). The classifiers will be developed assuming knowledge of the target class (UXOs) only, assuming little or no information concerning the infinite class of false targets. Moreover, the focus will be primarily on small- and medium-sized UXO (since the large ordnance will generally be excavated in any case).				
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I. List of Manuscripts Submitted/Published under ARO Support

1. Y. Zhang, L. Collins, H. Yu, C. Baum and L. Carin, "Sensing of unexploded ordnance with magnetometer and induction data: Theory and signal processing," *IEEE Trans. Geoscience Remote Sensing*, vol. 41, pp. 1005-1015, May 2003.
2. Y. Zhang, L. Collins and L. Carin, "Unexploded ordnance detection using Bayesian physics-based data fusion", *Integrated Computer-Aided Engineering*, Vol.10, pp. 231-247, July 2003.
3. Y. Zhang, X. Liao and L. Carin, "Detection of buried targets via active selection of labeled data: application to sensing subsurface UXO," *IEEE Trans. Geosc. Remote Sensing*, vol. 42, pp. 2535-2543, Nov. 2004.

II. Scientific Personnel

Faculty: Lawrence Carin (PI) and Leslie Collins
Post-doc: Zhijun Liu and Yan Zhang

III. Invention Reports

None.

IV. Scientific Progress and Accomplishments

We have developed a dipole-based model for wideband induction data, appropriate for both frequency- and time-domain data. In particular, for rotationally symmetric targets, with axis of rotation aligned along the z axis, we have demonstrated that the EMI magnetization tensor can be expressed as

$$\mathbf{M}(\omega) = \mathbf{zz}[m_z(0) + \sum_k \frac{m_{zk}}{\omega - j\omega_{zk}}] + (\mathbf{xx} + \mathbf{yy})[m_p(0) + \sum_i \frac{\omega m_{pi}}{\omega - j\omega_{pi}}] \quad (1)$$

where $m_z(0)$ and $m_p(0)$ are respectively the longitudinal and transverse components of the static magnetic response (each zero for non-ferrous targets); ω represents the angular frequency; $j\omega_{zk}$ represents the k th z -directed EMI dipole resonant frequency, with $j\omega_{pi}$ similarly defined for the dipoles perpendicular to z ; the EMI dipole-moment strengths are denoted m_{zk} and m_{pi} ; and \mathbf{x} , \mathbf{y} and \mathbf{z} represent x -, y - and z -directed unit vectors. In this model each of the principal axes (parallel and perpendicular to z) are represented in terms of characteristic dipoles (often only the lowest-order dipole mode in each direction is important, although above we represent a summation of such modes), with each dipole represented by an associated *imaginary* resonant frequency. When one converts the above frequency-domain magnetization to the time domain, the imaginary resonant poles yield the damped-exponential time-domain response characteristic of a transient EMI system. This parametric representation is well suited to signal processing, since the model parameters extracted from measured data are applicable to a Bayesian processor.

Our model has been applied thus far to simple, isolated UXO. There are many cases for which one would be interested in more-complicated targets. In the context of individual UXO, many ordnance are composed of multiple parts (body, rings, fins, etc.) each of which may contribute its own dipole response to the composite signature. In the proposed research we will extend the above EMI resonant-dipole model to the case of targets with multiple parts. In general each target component will have an associated EMI dipole, each with a unique physical location (tied to the position of the part). In our initial model, developed to date for simpler targets, the dipoles have implicitly been positioned at or near the target center. The situation is more complicated when considering UXO of more-general composition.

For the wideband induction data, either in the frequency- or time-domain, we utilize the model in (1) to extract EMI features from the data. In particular, features of interest include ratios of the dipole moments m_{zk} and m_{pi} , the dipole resonant frequencies, and the goodness of fit (GOF) of the model to the data. While extracting these features from the spatial EMI data, one is often beset by problems associated with local minima. In other words, multiple realizations of the EMI model yield good fits to the data. However, by constraining the EMI inversion (model fit) by the results of the magnetometer inversion (e.g. depth), we significantly improve overall inversion performance.

Assume that the features from the model are denoted by the vector \mathbf{x} , with these features extracted from the magnetometer and wideband EMI models, as discussed above. We perform classification of the target by employing the likelihood ratio

$$\lambda = \frac{p(\mathbf{x}|\mathbf{H}_1)}{p(\mathbf{x}|\mathbf{H}_0)} \quad (2)$$

where $p(\mathbf{x}|\mathbf{H}_1)$ and $p(\mathbf{x}|\mathbf{H}_0)$ represent the likelihood that the features \mathbf{x} came from a target (hypothesis \mathbf{H}_1) and from clutter (hypothesis \mathbf{H}_0), respectively.

With regard to modeling the likelihoods $p(\mathbf{x}|\mathbf{H}_1)$ and $p(\mathbf{x}|\mathbf{H}_0)$, we will explore a parametric approach in which we model these distributions as N -dimensional Gaussian distributions, assuming that the feature vectors (extracted from the EMI and magnetometer data) are of dimension N . Under this assumption we utilize the available training data to estimate the mean value of \mathbf{x} under hypotheses \mathbf{H}_1 and \mathbf{H}_0 . Moreover, the training data is utilized to compute the associated $N \times N$ covariance matrices.

We will also investigate non-parametric means of performing classification based on the feature vectors \mathbf{x} , under which we do not require assumptions concerning the statistical properties of the data (*i.e.* we do not have to make the Gaussian assumption). We will employ kernel-based algorithms, in which the feature vector \mathbf{x} is processed via the scalar operator

$$y(\mathbf{x}) = \sum_{m=1}^M w_m g(\mathbf{x}, \mathbf{x}_m) + b \quad (3)$$

where \mathbf{x}_m denote the feature vectors from the M training examples, w_m are weights, b is an offset or bias, and $g(\mathbf{x}, \mathbf{x}_m)$ is a general nonlinear function that quantifies the similarity of the feature vector with available training data. The function $g(\mathbf{x}, \mathbf{x}_m)$ is often termed a “kernel”, an example of which is the radial basis function (RBF)

$$g(\mathbf{x}, \mathbf{x}_m) = \exp(\|\mathbf{x} - \mathbf{x}_m\| / \sigma^2) \quad (4)$$

where $\|\mathbf{x} - \mathbf{x}_m\|$ is a general norm quantifying the “distance” in feature space between \mathbf{x} and \mathbf{x}_m .

It is also important to note that the parametric EMI model summarized in equation (1) is appropriate for both time- and frequency-domain induction sensors. Therefore, in addition to processing data from frequency-domain systems, such as the GEM-3, we will also process available time-domain data provided by the sponsor. For the case of time-domain sensors, the imaginary resonant frequencies in (1) are transformed into exponential decay constants. The other parameters of the model, such as the dipole-moment strength, have the same meaning in both a time- and frequency-domain implementation. From a practical standpoint, however, a time- or frequency-domain sensor may be optimal for a given sensing scenario. For example, for large UXO the resonant frequencies in (1) may be too low (small) to measure via a frequency-domain system, and therefore a time-domain system may be preferable. In a time-domain system these low resonant frequencies correspond to a long late-time EMI decay constant. This is easily measured via a time-domain system with a long enough time window. By contrast, small UXO are better measured via a frequency-domain system, since the late-time decay is very fast for such targets (often too fast to be measured via a time-domain system). Since we often do not know *a priori* whether the target is large or small, this suggests classification based on fusing time- and frequency-domain EMI data. This will be pursued in the proposed research (using data provided by the sponsor).

V. Technology Transfer

The software developed under this program is being transitioned to the US Army Corps of Engineers (Vicksburg, MS)